DOE DATA DAYS 2022

APPFL

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APPFL: OPEN-SOURCE FRAMEWORK FOR PRIVACY-PRESERVING FEDERATED LEARNING

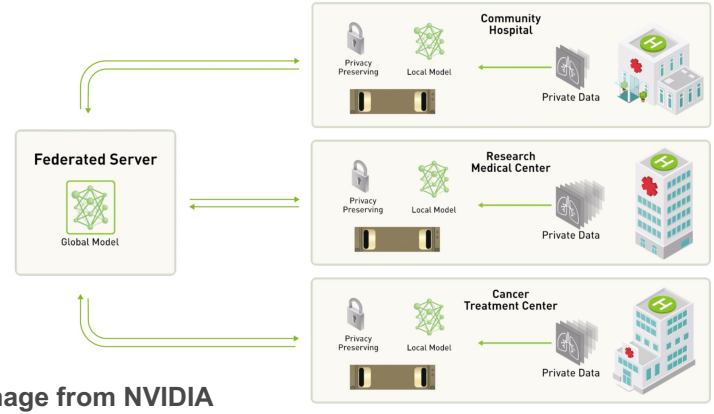

Image from NVIDIA

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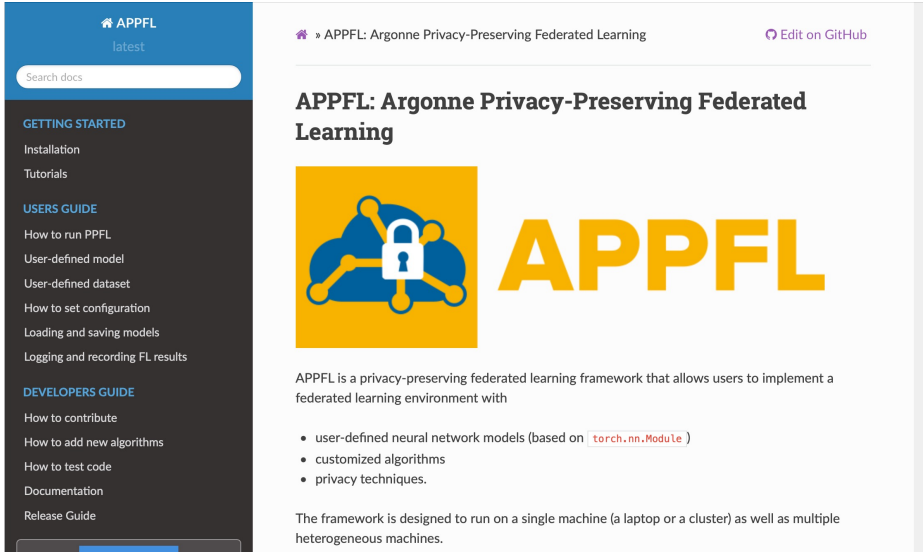
APPFL: ARGONNE PRIVACY-PRESERVING FEDERATED LEARNING

Open-source PPFL framework

- Motivations
  - Distributed data from multiple institutions (e.g., Argonne, UChicago, etc.)
  - Avoid data transfer to a server
  - Potentially sensitive/private data
- Science applications
  - Biomedical data
  - Smart meters deployed in grid
  - Experimental facilities (e.g., APS X-ray beamlines)
  - National security (e.g., critical infrastructure)



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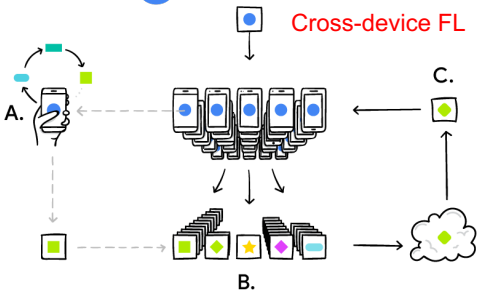
FEDERATED LEARNING

- Machine learning without centralizing training data
  - No direct data sharing or storing
- More benefits
  - Learning a global/shared model
  - Utilizing a localized model at each client side
  - Personalization
- Two settings:
  - Cross-device FL (1000s and 1Ms of small devices)
  - Cross-silo FL (a few large data repositories)

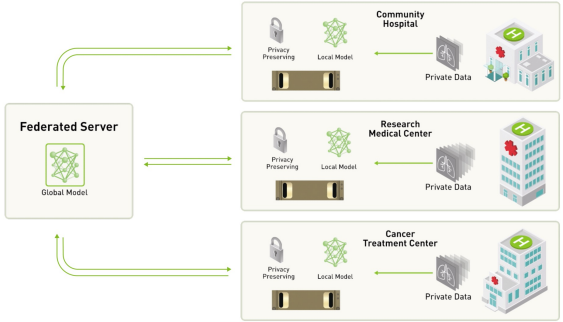
Google

Cross-device FL



Your phone personalizes the model locally, based on your usage (A). Many users' updates are aggregated (B) to form a consensus change (C) to the shared model, after which the procedure is repeated. (image from Google)

Cross-silo FL



Federated learning on decentralized medical datasets (image from NVIDIA)

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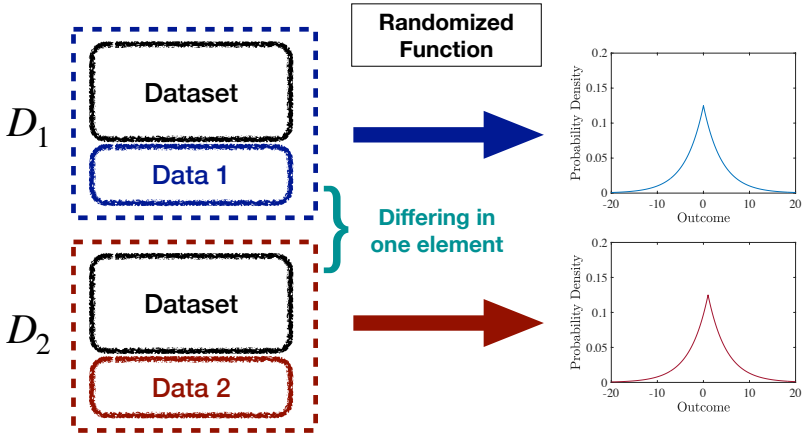
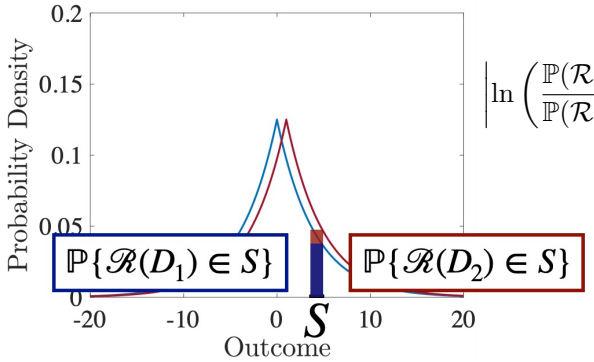
PRIVACY-PRESERVING TECHNIQUES

- **Some techniques in FL**
  - Homomorphic encryption: limited to certain operations
  - Secure multi-party computation: computationally expensive
  - Differential privacy: potential accuracy loss
- **Differential Privacy**
  - The two outcomes are indistinguishable for all D1 and D2 which differ in one individual's data.





$$\left|\ln\left(\frac{\mathbb{P}(\mathcal{R}(D_1) \in S)}{\mathbb{P}(\mathcal{R}(D_2) \in S)}\right)\right| \leq \epsilon$$

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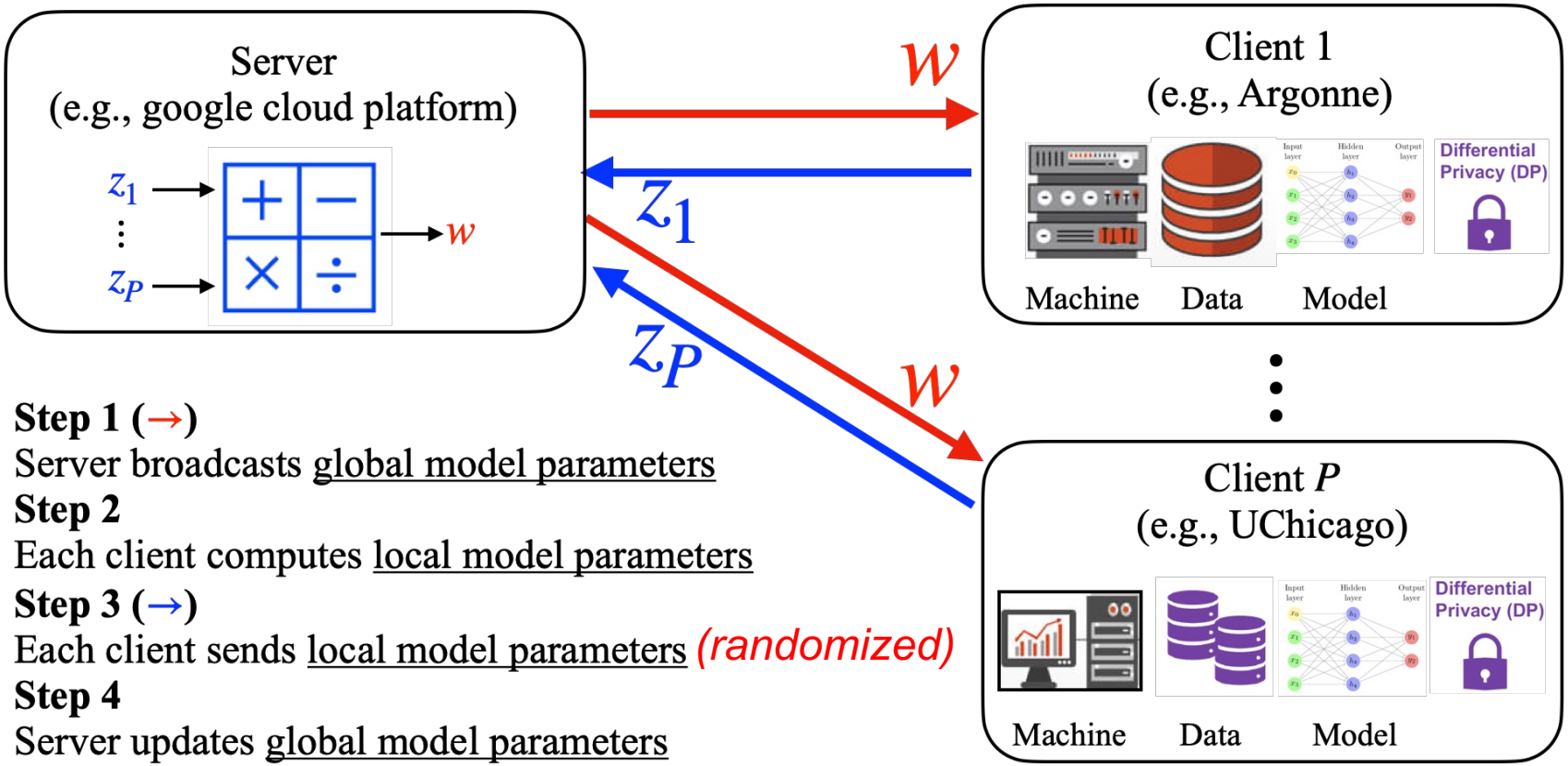
OVERVIEW: APPFL FRAMEWORK



Step 1 (→)
Server broadcasts global model parameters
Step 2
Each client computes local model parameters
Step 3 (→)
Each client sends local model parameters *(randomized)*
Step 4
Server updates global model parameters

MAJOR COMPONENTS OF APPFL

- **Training algorithms:**
  - IIADMM, FedAvg [McMahan et al., 2017], ICEADMM [Zhou and Li, 2021]
  - Any user-defined FL algorithms can be added.
- **Differential privacy**:
  - Random perturbation with Laplacian noises [Dwork et al., 2006]
  - More advanced schemes can be added.
- **Communication protocols**:
  - gRPC: communication between multiple platforms and languages
  - MPI: efficient communication in a cluster environment
- **User-defined model and data:**
  - Inherits PyTorch's neural network module, torch.nn.Module
  - Dataset class that inherits the PyTorch's Dataset

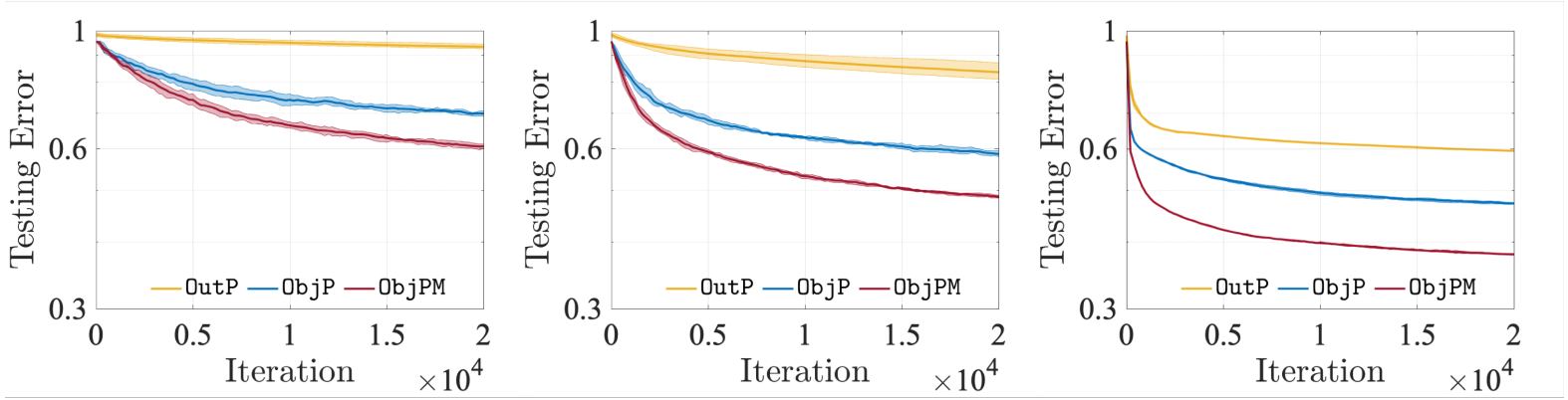
ADVANCED PPFL ALGORITHMS

Implementation of novel training algorithms

- (state-of-the-art) OutP: Inexact ADMM (IADMM) + output perturbation
- (APPFL) ObjP: IADMM + objective perturbation
- **(APPFL) ObjPM:** IADMM + objective perturbation + multiple local updates

Stronger privacy
Weaker learning

Weaker privacy
Stronger learning



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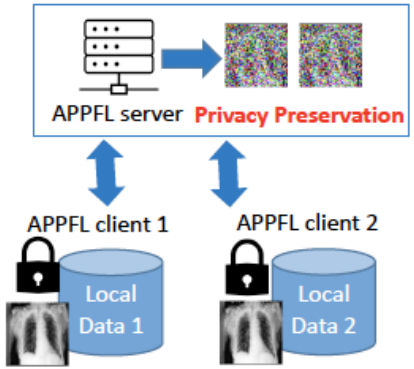
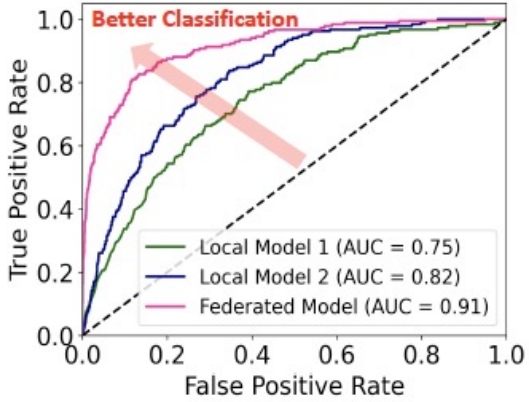
USE CASE

Chest X-ray classification for COVID-19 cases

- FL can produce more accurate model, compared to the models trained on local datasets.
- DP is applied to protect chest X-ray data from reverse-engineering the model gradients communicated during training.
- Collaborations with UChicago Medical School and Broad Institute

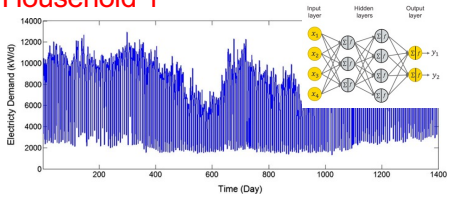




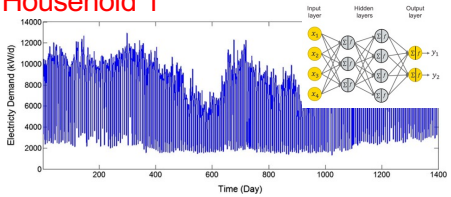
USE CASE

Federated load forecasting for electric distribution system

Household 1

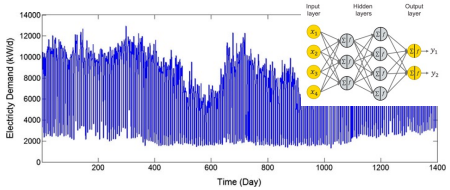


Household 1



⋮

Household *N*



Parameters with differential privacy

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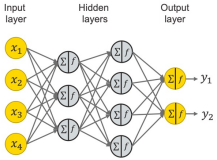

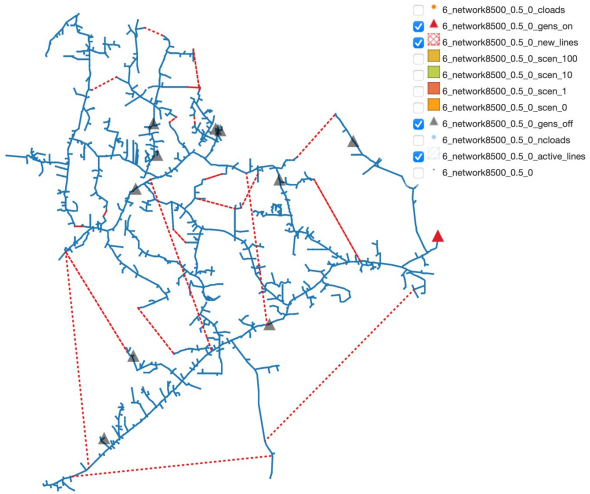

- Electricity consumption at household level
- Distributed data at a large number of devices
- Privacy concern

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CONCLUDING REMARKS

- APPFL: open-source Python package with support of any Pytorch models
  - The package has been released (v0.2.0).
- Any user-defined ML model can be trained on decentralized data while ensuring data privacy.
- Customized PPFL algorithms can be easily implemented.
- Applications: national security, smart grid (Fig. 1), biomedicine, experiments (Fig. 2), etc.
- Collaborations and contributions are welcome!

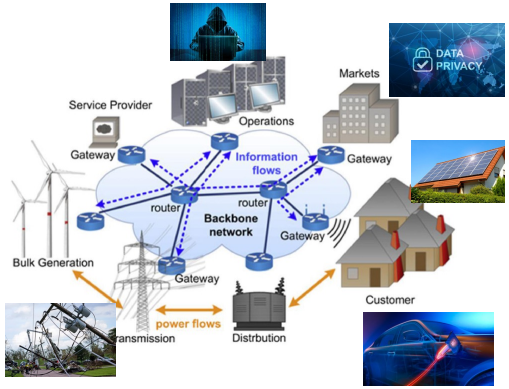

Fig 1. Network architecture in smart grid (modified from https://doi.org/10.1016/j.comnet.2012.12.017)

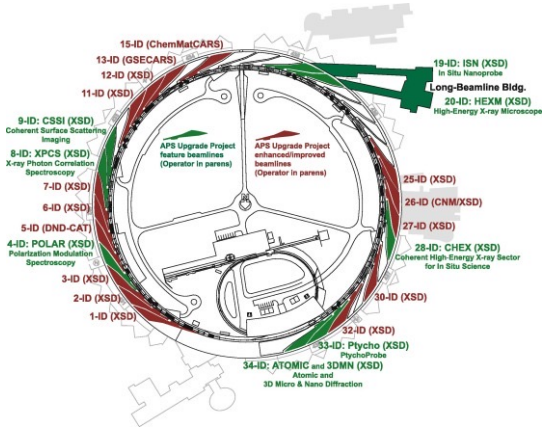

Fig 2. Multiple experimental devices at APS

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- Minseok Ryu, Youngdae Kim, Kibaek Kim, and Ravi Madduri. “APPFL: Open-Source Software Framework for Privacy-Preserving Federated Learning” *arXiv preprint arXiv:2202.03672. (accepted to IPDPS 2022)*, 2022
- Minseok Ryu and Kibaek Kim. “A Privacy-Preserving Distributed Control of Optimal Power Flow” *IEEE Transactions on Power Systems 37(3)*, 2022
- https://github.com/APPFL

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- Nick Dodd (ASU)

THANK YOU